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Dose urban landscape pattern affect CO_2 emission efficiency? Empirical evidence from megacities in China

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ABSTRACT

In addition to socioeconomic factors, urban morphology is increasingly being recognized for the potential role it might play in tackling climate change. Meanwhile, improving CO_2 emission efficiency has become a significant aim in reducing CO_2 emissions without sacrificing economic development. Hence, investigating the effects of urban landscape pattern on CO_2 emission efficiency is of great importance. As thus, this study is designed to quantitatively estimate the associations between urban landscape pattern and CO_2 emission efficiency, using panel data for five megacities in China in the period 1990–2013. A series of landscape metrics were first selected to quantify three dimensions of urban landscape pattern, namely urban expansion, urban shape complexity, and urban compactness. CO_2 emission efficiency was then evaluated using three quantitative indicators, namely per capita CO_2 emission, CO_2 emission intensity, and CO_2 emission performance. Finally, panel data models were performed to estimate the influences of urban landscape pattern on CO_2 emission efficiency. The results demonstrate that both urban expansion and urban shape complexity inhibited the improvement of CO_2 emission performance. In addition, urban compactness was found to be conducive to the reduction of CO_2 emission per capita and CO_2 emission intensity, as well as the improvement of CO_2 emission performance. The findings obtained through this study cast a new light on the significance of city planning and the optimization of spatial structure in improving CO_2 emission efficiency, providing decision makers and urban planners with a scientific basis from which to approach the task of reducing CO_2 emissions whilst maintaining economic development.
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1. Introduction

Global warming, which is characterized by rising temperatures and anomalous climatic events (Grimm et al., 2008), has become a severe threat to sustainability (Li et al., 2016). Increasing atmospheric carbon dioxide (CO_2) is believed to be closely related to climate change, especially global warming (Malik et al., 2016). Atmospheric CO_2 is affected by both carbon sources and carbon sinks. Carbon sources are mainly anthropogenic carbon emissions, and carbon sinks are a number of terrestrial and ocean processes that remove CO_2 (Canadell et al., 2007). Scientists have been studying this geoscience issue for some time. From the perspective of carbon sources, the combustion of fossil fuels and emissions from Land-use change (LUC) constitute the two most critical ones. As economic development is highly dependent on energy consumption, especially fossil fuels, the global gross domestic product (GDP) growth is believed a key factor of the increasing CO_2 emissions (Raupach et al., 2007). LUC emissions, another important source of atmospheric CO_2, mainly include emissions due to deforestation and intensive cultivation of cropland, which are connected with not only the current situations but also the carry-over effects of previous situations (Le Quéré et al., 2009). From the perspective of carbon sinks, approximately half of the anthropogenic CO_2 emissions are estimated to be offset by the terrestrial and ocean absorption every year (Reay et al., 2007; Sitch et al., 2015). Terrestrial vegetation withdraw atmospheric carbon through photosynthesis, as thus, afforestation is an effective way to increase carbon sequestration (Foody et al., 1996). In addition to terrestrial ecosystems, the ocean also plays an important role in CO_2 uptake (Landschutzer et al., 2014), and about one quarter of the

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anthropogenic CO_2 emissions were absorbed by the ocean in the last twenty years (Le Quéré et al., 2014). It's important to note that terrestrial vegetation and the ocean not only absorb but also release CO_2, and they are regarded as net sinks for atmospheric CO_2 because the absorption exceed the production globally. Whether they act as carbon sources or carbon sinks depends on the geophysical, biological, and climatic conditions (Reichstein et al., 2013; Schimel et al., 2015). For example, a high air-to-water CO_2 flux exists in the coastal ocean, which at different latitudes have varying sources and sinks of carbon. Specifically, low-latitude coastal ocean emit CO_2 as they receive the majority of the terrestrial organic carbon, while high- and mid-latitude ones absorb CO_2 (Bauer et al., 2013; Cai, 2011). Apparently, it is more complete to take both the emission and absorption of CO_2 into account, however, it is a fairly intricate issue and makes this study hard to execute. Hence, for simplification of the analysis, only CO_2 emissions production were considered, which was taken as a possible limitation in the application of climate science to the overall problem facing urbanization. The anthropogenic combustion of fossil fuels, especially in urban areas, is believed to be the primary source of global CO_2 emissions (IPCC, 2007), and it has been estimated that urban areas consume more than two thirds of global energy and emit more than 70% of the world's CO_2 (IEA, 2012). It is therefore significant to reduce the CO_2 emissions generated by cities for tackling global climate change (Wang et al., 2017). Nevertheless, urban areas also contribute greatly to global economic development, reducing CO_2 emissions in urban areas while keeping the momentum of economic development thus constitutes a dual challenge for governments internationally. Improving CO_2 emission efficiency is a significant aim in reducing CO_2 emissions without sacrificing economic development, studies addressing the influencing factors of CO_2 emission efficiency have, as a result, become increasingly important.

The sustainable development of regions throughout the world requires a better understanding of “urban landscape pattern” (Chang et al., 2011), a term that describes the spatial interaction among landscape factors in urban areas. Particularly, it addresses landscape configuration with respect to size, shape complexity, and compactness (Forman and Godron, 1986). A city's urban landscape pattern influences how it can expand and how its land use, transport, and infrastructure can be configured (Tsai, 2005). Different urban landscape patterns may induce disparate social, ecological, and environmental consequences (Holden, 2004; Wachs, 1993). Recently, it has become an intriguing topic to explore the potential role urban landscape pattern might play in CO_2 emission reduction. In general, existing studies focused on three aspects of urban landscape pattern: urban sprawl, urban shape complexity, and urban compactness. Taking 142 U.S. cities as a sample, Hankey and Marshall (2010) examined the paths by which urban form impacts on the emission of greenhouse gases from passenger vehicles, finding urban infill development to be associated with a reduction in CO_2 emissions from passenger vehicles through the impact it exerts upon people's daily travel patterns (Hankey and Marshall, 2010). Similar research was conducted by Ma et al. (2015) (Ma et al., 2015), who concluded that job densities, retail densities, and mixed land uses had inhibitory effects on residents' commuting activities, and consequently led to fewer CO_2 emissions. As to household CO_2 emissions, Lee and Lee (2014) have examined the impacts of urban form on household CO_2 emissions in the 125 largest urbanized areas in America, finding that urban sprawl was positively correlated with urban household energy-related CO_2 emissions (Lee and Lee, 2014), which is consistent with the finding of an empirical investigation undertaken in relation to China by Ye et al. (2015) (Ye et al., 2015). Urban shape complexity is generally believed to have positive impacts on CO_2 emissions. For example, Makido et al. (2012) (Makido et al., 2012) estimated the association between urban form and CO_2 emissions for 50 Japanese cities, concluding that less urban shape complexity lower residential CO_2 emissions. Decentralized development could increase mobility, commuting, and thus subsequently even CO_2 emission tonnages (Wang et al., 2014). Liu and Sweeney (2012), taking the Greater Dublin Region for example, explored the association between household energy-related CO_2 emissions and land-use characteristics, finding that dispersion could significantly increase energy-related CO_2 emissions (Liu and Sweeney, 2012). Working in the context of the U.K., Banister (1996) (Banister, 1996) found that compact development help to reduce CO_2 emissions. These results are supported by the findings of studies undertaken in relation to Finland by Harmaajarvi et al. (2002) (Harmaajarvi et al., 2002).

Although previous literature have explored the impacts of urban landscape pattern on CO_2 emissions and provided quite insightful viewpoints from which to view this issue, several flaws still exist in previous studies. Firstly, CO_2 emission tonnage was used as dependent variable by most studies, while the effects of urban landscape pattern on CO_2 emission efficiency have not been adequately addressed in the literature to date. Actually, improving CO_2 emission efficiency is a key aspect of CO_2 emission reduction, without sacrificing economic development. Broadly speaking, the concept of “CO_2 emission efficiency” refers to the economic or other desirable outputs that can be gained as the results of processes that generate CO_2 emissions (Tahara et al., 2005). Higher CO_2 emission efficiency quite simply means more beneficial outputs with less accompanying CO_2 emissions (Liu et al., 2014). Although CO_2 emission efficiency can be defined from multiple perspectives, three indicators are commonly used to represent it at the macro-level, among which CO_2 emission per capita and CO_2 emission intensity are two single-factor and ratio-based indicators which refer to the CO_2 emission per person and per unit currency output (e.g., per unit GDP). Additionally, a total-factor indicator, called CO_2 emission performance, is popularly calculated using data envelopment analysis (DEA) to measure CO_2 emission efficiency. The factors influencing CO_2 emission efficiency have drawn much scholarly attentions, and a range of socioeconomic factors have been identified by existing studies, such as industrial structure (Iftikhar et al., 2016), energy consumption structure (Moutinho et al., 2015), urbanization (Peters et al., 2007), and exports (Stretesky and Lynch, 2009). However, urban landscape pattern was barely identified as one of the factors affecting CO_2 emission efficiency. Secondly, the majority of previous studies analyzed urban landscape pattern from a single perspective, i.e., only one of the three dimensions of urban landscape pattern was used as explanatory variable, while limited number of literature integrated the three dimensions of urban landscape pattern and conducted comprehensive analysis. Thirdly, literature regarding developed economies (e.g., the U.S. and Europe) are plentiful, while the impacts of urban landscape pattern on CO_2 emission in developing economies like China still remain relatively unexplored.

Since previous studies have generally failed to provide adequate and explicit evidence of how urban landscape pattern to affect CO_2 emission efficiency, the innovations and potential contributions of the present study can be addressed as follows. First and foremost, this study investigated the effects of urban landscape pattern on CO_2 emission efficiency for the first time, extending the influencing factors of CO_2 emission efficiency from socioeconomic factors to urban morphology factors. Furthermore, the three dimensions of urban landscape pattern, i.e., urban expansion, urban shape complexity, and urban compactness, were taken into account simultaneously, rather than focusing on one of them alone. Likewise, three different indicators, including CO_2 emission per capita, CO_2 emission intensity, and CO_2 emission performance, were

simultaneously used to evaluate CO_2 emission efficiency from diverse perspectives, instead of single measurement. In this way, the role different features of urban landscape pattern played in different measurement of CO_2 emission efficiency can be disentangled. Last but not the least, as a study regarding China, the largest developing country in the world, this study would enriched the perception of urban landscape pattern's implications for CO_2 emission.

In order to explore the impacts of urban landscape pattern on CO_2 emission efficiency, the present study was designed. China's five most rapidly developing megacities (Beijing, Tianjin, Shanghai, Chongqing, and Guangzhou) were selected as study area, which undergo a range of environmental issues related to climate change and generate increasing CO_2 emissions, as the study areas for this research. Urban landscape pattern was first quantified and analyzed utilizing a range of landscape metrics and remote sensing land use data, which formed the independent variables of the study. CO_2 emission tonnages from the combustion of fossil fuels were then estimated, utilizing energy consumption data and emission coefficients recommended by the Intergovernmental panel on climate change (IPCC). On the basis of this estimation, three different indexes representing CO_2 emission efficiency were then computed, which constituted the dependent variables of the study. After completing these calculations, a number of panel data models were implemented to estimate whether and to what extent urban landscape pattern is associated with CO_2 emission efficiency. The results of this study provide a reference for decision makers to build low-carbon cities, and offer basic principles of sustainable urban planning for urban planners.

2. Study area

This study focused on five megacities in China: Beijing, Tianjin, Shanghai, Chongqing, and Guangzhou, which are broadly situated in different regions of China (Fig. 1). Four municipalities in China (i.e., Beijing, Tianjin, Shanghai, and Chongqing) are all selected as study objects of this study as they are directly administrated by the central government and thus become not only the largest but also the most rapidly developing cities in China. As the capital of China, Beijing is the national center of politics, culture and transportation. Tianjin, which borders Beijing and the Bohai Gulf, is China's largest northern coastal city. Located in the Yangtze River Delta, Shanghai is China's economic, financial, and innovation center and has the largest population of all Chinese cities. Chongqing is the only municipality in West China, as well as the regional economic and transportation center for the upper Yangtze River. Since aforementioned four municipalities are all situated in Northern China, Eastern China, or Western China, Guangzhou, the largest city in Southern China, was furthermore chosen, as the representative of fast-growing megacities in Southern China. In this study, urban area was defined as spatial functional unit, rather than spatial administrative unit, i.e., it was urban built-up area instead of urban administrative area that was studied. The administrative area of Chongqing was larger than those of other four megacities, however, Chongqing had a relatively small urban built-up area, which ensured the comparability across different cities (see Fig. 5). Therefore, it is suitable to take Chongqing together with other four megacities as study area.

One of the reasons why these five megacities were chosen is that they all experienced significant variations of urban landscape pattern duo to the continuing process of urbanization and industrialization. Specifically, substantial amounts of farmland and unused land were converted to urban development land. According to a previous estimation (Fang et al., 2015), the five megacities selected in this study had the largest and the fastest-growing urban built-up areas among 30 provincial capital cities in China. To be more specific, they were contrasted with the five smallest provincial capital cities (i.e., Nanchang, Guiyang, Yinchuan, Xining, and Haikou). As shown in Fig. 2(a), the urban built-up areas of the five megacities studied were much larger than those of their antithetical cities in both 1990 and 2010. Moreover, previous studies also demonstrated that urban shape complexity and urban compactness varied with different cities in China, due to regional disparity (Fang et al., 2016; Zhou and Ye, 2013). Since the five megacities used in

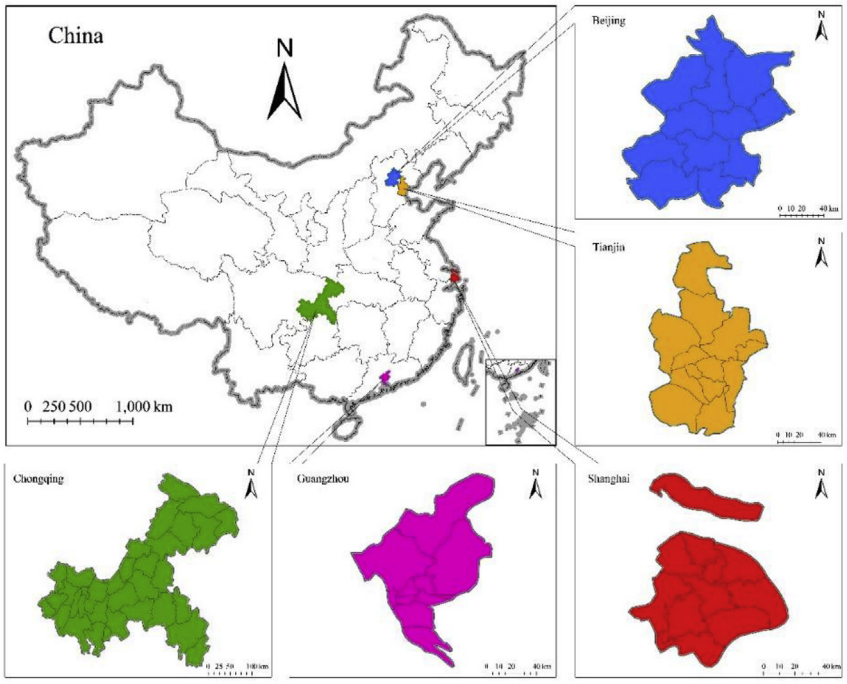

Fig. 1. Location of the study areas.

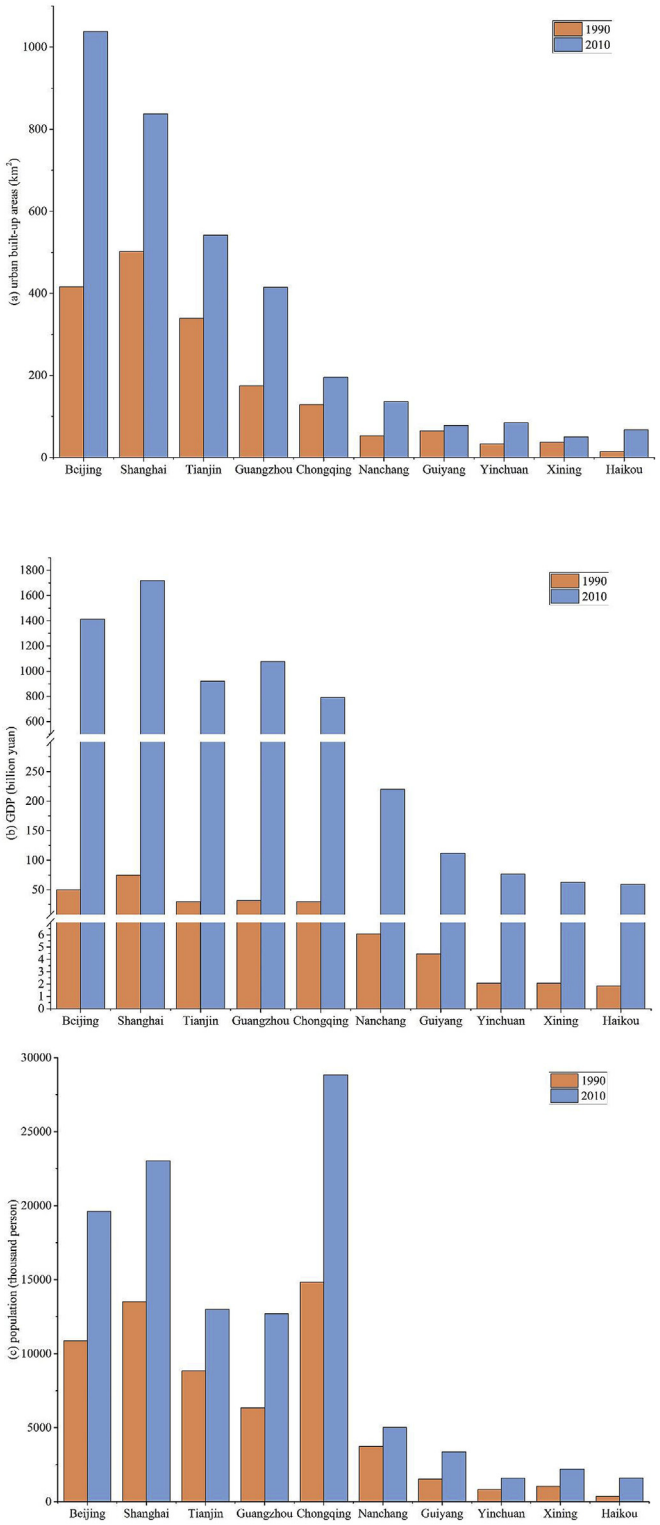

Fig. 2. Urban built-up areas (a), GDP (b), and population (c) of five megacities studied and their antithetical cities. Data source (Fang et al., 2015): and China City Statistical Yearbook (1991 and 2011).

this study had higher development levels than other Chinese cities, their urban shape complexity and urban compactness basically evolved faster. In a word, the urban landscape patterns in the five megacities studied have gone through tremendous changes, which have received widespread attentions from many researchers (Fan and Fan, 2014; Fung et al., 2008; Li and Liu, 2017; Yue et al., 2014; Zheng et al., 2017).

Another important reason for selecting these five megacities is that they are China's leading powerhouses since the reform and opening up in 1978, which constitute the fastest-developing as well as the largest cities in China, while suffering from a series of environmental issues. As shown in Fig. 2(b) and (c), the five antithetical cities' GDP and population were much smaller and slower-growing, which provided a stark contrast to the five megacities studied. GDP and population have been identified as two key anthropogenic factors in determining CO_2 emissions by plenty of studies, as thus, the five megacities used in this study have greater demands for energy consumption and thus produce more CO_2 emissions, which poses a bigger challenge to their sustainability.

To sum up, as the most rapidly growing cities in China, the five megacities underwent both significant changes of urban landscape pattern and noticeable increases in CO_2 emissions, because of which it is clearly of great significance to identify the association between urban landscape pattern and CO_2 emission efficiency in these fast-growing cities for policy makers and urban planners to curb CO_2 emission and climate change through fostering low-carbon and sustainable urban development. Hence, five Chinese megacities, including Beijing, Tianjin, Shanghai, Chongqing, and Guangzhou, were selected as the research areas in this study.

3. Methods and materials

3.1. Quantifying urban landscape pattern by combining landscape metrics and remote sensing data

Remote sensing technology presents an effective way to obtain urban land-use data (Herold et al., 2002). To extract urban land-use areas for each of the study areas, land-use data from Landsat ETM scenes and Landsat TM scenes with a spatial resolution of 30 m × 30 m for six periods (1990, 1995, 2000, 2005, 2010, and 2013) were utilized, which was developed by the Institute of Geographical Sciences and Natural Resources Research (IGSNRR, http://www.igsnrr.ac.cn) at the Chinese Academy of Sciences (CAS). Detailed processes for extracting urban land use can be seen in relevant literature (Fang et al., 2015; Ou et al., 2013). In order to test the reliability of the land-use classification results, the Kappa coefficient technique was performed, which was a widely-utilized accuracy measurement for remote sensing image interpretations. Since the Kappa coefficients for all images were greater than 0.85, it could be concluded that the urban land-use data used in this study was quite reliable. Fig. 3 set out the spatial patterns of urban expansion in each of the five megacities from 1990 to 2013.

With the development of geographic information systems (GIS) and remote sensing (RS), landscape metrics have proved effective means for evaluating landscape patterns (Leitão and Ahern, 2002; Smiraglia et al., 2015; Su et al., 2012). Urban landscape pattern is viewed here as the spatial configuration of an urban area, consisting of three dimensions: size, shape, and aggregation (Cabral and Costa, 2017; Chapman, 2017; Cirilli and Veneri, 2013). In accordance with relevant studies (Aguilera et al., 2011; Bereitschaft and Debbage, 2013; Fan and Myint, 2014; Herold et al., 2003; Huang et al., 2007; Luck and Wu, 2002; Seto and Fragkias, 2005; Tv et al., 2012), seven frequently-used landscape metrics were selected to quantify urban landscape pattern: total area (TA), perimeter-area fractal dimension (PAFRAC), area-weighted mean shape index (AWMSI), landscape shape index (LSI), patch density (PD), landscape division index (DIVISION), and splitting index (SPLIT). Based on the definitions and the features of these seven landscape metrics, they were subsequently categorized into three dimensions: urban expansion, urban shape complexity, and urban

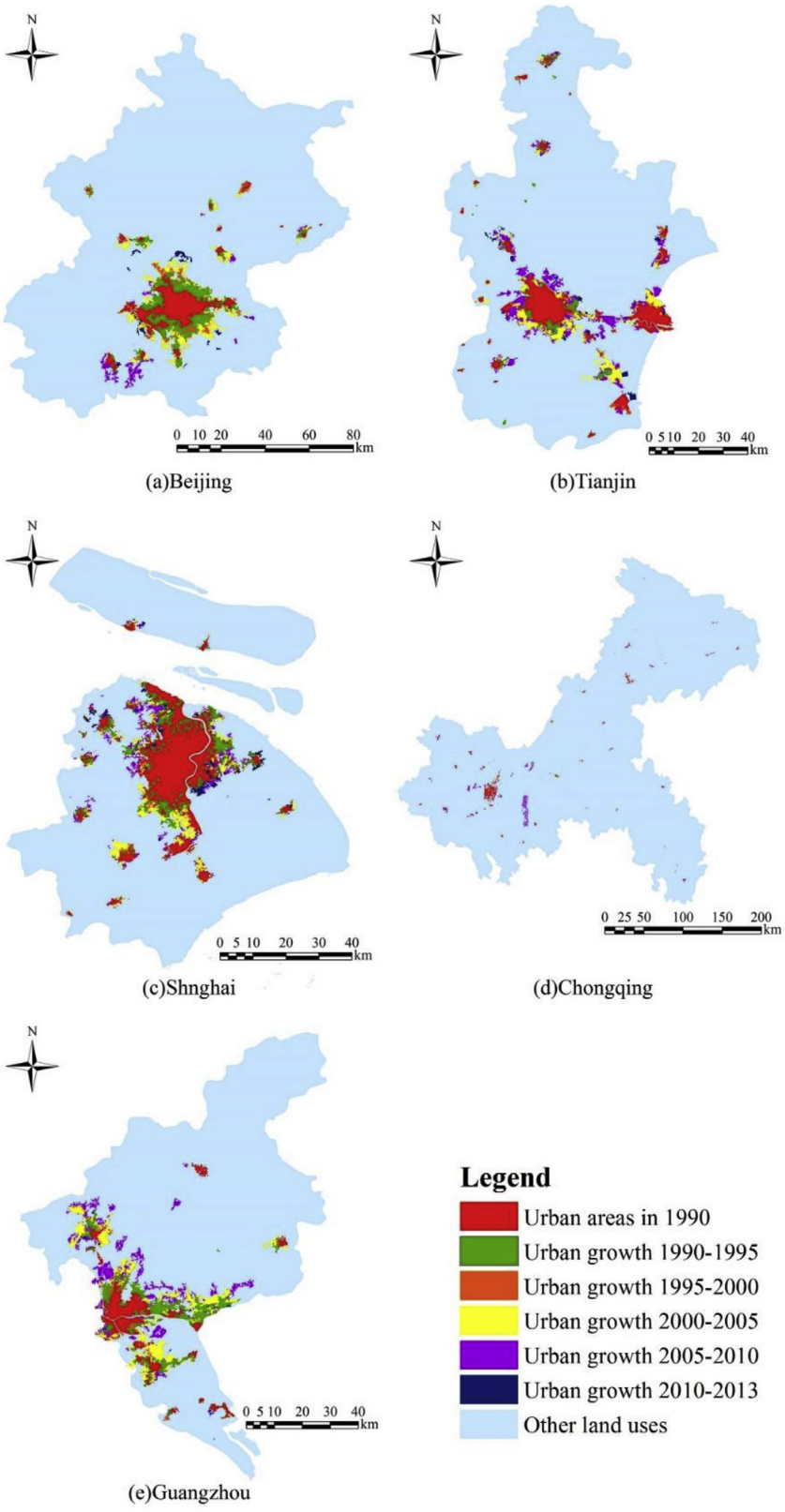

Fig. 3. Changes in urban land use in Beijing (a), Tianjin (b), Shanghai (c), Chongqing (d), and Guangzhou (e), 1990–2013.

compactness. TA, which equals the total area of all patches, is an important indicator for characterizing the overall size and the expansion of a given landscape and also the foundation of calculating other spatial metrics (Fang et al., 2016). It is generally recognized that urban areas continually increase in line with urban growth. The shape complexity of urban patches was represented by PAFRAC, AWMSI, and LSI. The value range of PAFRAC is 1–2, and the shape of landscape becomes more convoluted with the increase of the value of PAFRAC (Dietzel et al., 2005). AWMSI or LSI equals 1 when the landscape has the most regular shape, and increases as the complexity of landscape shape increases (Huang et al., 2009; Wu et al., 2011). In a word, the greater irregularity the shape of the landscape, the higher the values of PAFRAC, AWMSI, and LSI. PD, DIVISION, and SPLIT reveal the compactness of urban patches. PD, which is generally utilized to reflect the subdivision of a landscape, denotes the quantity of patches, divided by the total area of all patches (Deng et al., 2009). DIVISION, which reflects the fragmentation of landscape, equals the possibility that two randomly selected pixels are not located in the same patch. SPLIT indicates the scatter of urban patches. Specifically, the more compact the urban landscape, the lower the values of PD, DIVISION, and SPLIT. All the landscape metrics were calculated using FRAGSTATAS 4.2. Table 1 presents a more specific description of the seven metrics employed in this research, including the specific mathematical equations.

3.2. Evaluating CO_2 emission efficiency using multiple indicators

Current evidence suggests that the costal ocean, which generally act as localized CO_2 sinks, play an important role in the global carbon budget. However, the costal ocean can also act as emitters of CO_2, e.g., coastal areas bordering the South China Sea (Cai et al., 2006; Laruelle et al., 2018). As four of the five cities studied, except for Chongqing, are located in the coastal zone of China, they are subject to CO_2 accounting changes, e.g., sinks in and around Beijing, Tianjin, and Shanghai; and emitters in and around Guangzhou. Nevertheless, since this study investigated "emission efficiency", focusing on the CO_2 production component, the CO_2 absorption component and the broader CO_2 cycle were not taken into account. As thus, only the anthropogenic CO_2 emissions were calculated. Existing studies have conclusively indicated that the majority of the world's anthropogenic CO_2 emissions come from the burning of fossil fuels (Peters et al., 2012; Wang et al., 2015). As such, the energy-related CO_2 emissions for the five Chinese megacities studied were calculated for the years 1990, 1995, 2000, 2005, 2010, and 2013 using fossil fuels use data obtained from the China Energy Statistical Yearbook and the Guangzhou Statistical Yearbook, and CO_2 emission coefficients published by the IPCC (IPCC, 2006). Several indexes reflecting CO_2 emission efficiency have been proposed, among which CO_2 emissions per capita (Duro and Padilla, 2012; Huang and Meng, 2013), CO_2 emission intensity (Antanasijević et al., 2015; Bhattacharyya and Matsumura, 2010), and CO_2 emission performance (Wang et al., 2013a; Zhang et al., 2016) are the three most commonly used. The measure CO_2 emissions per capita averages total CO_2 emissions according to the total population of a region, and is used with the aim of minimizing the CO_2 emissions of each person. As income level rises, per capita CO_2 emissions exhibit a general upwards trend due to lifestyle transformations, indicating a decline in CO_2 emission efficiency. CO_2 emission intensity, which is another ratio-based indicator used to characterize CO_2 emission efficiency, is calculated by dividing total CO_2 emissions by GDP, aiming to minimize CO_2 emissions per unit of GDP. With economic development and technological progress, CO_2 emission intensity generally experiences a downwards trend, implying an improvement in CO_2 emission efficiency. Generally, it would be more suitable to estimate CO_2 emission per capita and CO_2 emission intensity using population and GDP of urban built-up areas. Unfortunately, such statistical data are not available, which calls for alternative method. Considering the fairly high levels of urbanization and industrialization of the five megacities in the present study, for each of them, population and GDP of the urban built-up areas constitute the vast majority of the aggregate population and the aggregate GDP, respectively. As thus, in accordance with previous studies (Chen et al., 2011; Huang and Meng, 2013; Liu et al., 2014), the aggregate population and the aggregate GDP were adopted as substitutive indicators to approximate CO_2 emission per capita and CO_2 intensity, which would not affect the major conclusions. Based on input-output analysis, CO_2 emission performance plays an important role in evaluating economic activity's efficiency in relation to CO_2 emissions, which aims to maximize desirable outputs (i.e., GDP) while minimizing inputs (i.e., capital, labor force, and energy) and undesirable outputs (i.e., CO_2 emissions).

3.2.1. CO_2 emission per capita

As it combines CO_2 emissions with population and therefore is significant in determining a region's CO_2 emission reduction share, CO_2 emissions per capita is a widely used indicator for evaluating CO_2 emission efficiency, which can be calculated using Eq. (1), as follows:

Table 1
Description of landscape metrics utilized in the study.

Category	Landscape metric	Equation	Description
Urban expansion	Total landscape area (TA)	$TA = \sum_{j=1}^{n} a_{ij}(1/10000)$	a_{ij} = area of patch ij
Urban shape complexity	Perimeter-area fractal dimension (PAFRAC)	$PAFRAC = \frac{2}{\frac{[N\sum_{i=1}^{m}\sum_{j=1}^{n}(\ln p_{ij}\cdot \ln a_{ij})] - [(\sum_{i=1}^{m}\sum_{j=1}^{n}\ln p_{ij})(\sum_{i=1}^{m}\sum_{j=1}^{n}\ln a_{ij})]}{(N\sum_{i=1}^{m}\sum_{j=1}^{n}\ln p_{ij}^2) - (\sum_{i=1}^{m}\sum_{j=1}^{n}\ln p_{ij})^2}}$	N = total number of patches in the landscape p_{ij} = perimeter of patch ij
	Area-weighted mean shape index (AWMSI)	$AWMSI = \sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(\frac{0.25p_{ij}}{\sqrt{a_{ij}}}\right)\left(\frac{a_{ij}}{A}\right)\right]$	A = total landscape area a_{ij} = area of patch ij
	Landscape shape index (LSI)	$LSI = \frac{0.25E^*}{\sqrt{A}}$	E^* = total length of edge in landscape A = total landscape area
Urban compactness	Patch density (PD)	$PD = \frac{N}{A}$	N = total number of patches in the landscape
	Landscape division index (DIVISION)	$DIVISION = 1 - \sum_{i=1}^{m}\sum_{j=1}^{n}\left(\frac{a_{ij}}{A}\right)^2$	a_{ij} = area of patch ij A = total landscape area
	Splitting index (SPLIT)	$SPLIT = \frac{A^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}a_{ij}^2}$	a_{ij} = area of patch ij A = total landscape area

$$EPC = \frac{CE}{P} \quad (1)$$

where *EPC* stands for CO_2 emissions per capita; *CE* is the amount of CO_2 emissions; and *P* represents population.

As indicated in Fig. 4(a), the CO_2 emissions per capita of five cities show an uptrend between 1990 and 2013, indicating a decrease in CO_2 emission efficiency. Chongqing had the lowest CO_2 emissions per capita, which increased moderately from 1.78 tons in 1990 to 6.09 tons in 2013. In 1990, the per capita CO_2 emissions of Shanghai was the highest (at 25.38 tons), however, by the year 2013, Tianjin had become the study area with the highest per capita CO_2 emissions, increasing from 19.86 tons in 1990 to 47.93 tons in 2013.

3.2.2. CO_2 emission intensity

As an essential component of the principle of "common but differentiated responsibilities" in CO_2 abatement, CO_2 emission intensity takes into account a region's actual level of economic development and can thus reflect a region's efforts to reduce CO_2 emission. It can be calculated using Eq. (2). GDP was adjusted to the constant price of the year 1990, in order to eliminate the effect of inflation.

$$EI = \frac{CE}{GDP} \quad (2)$$

where *EI* refers to CO_2 emission intensity; *CE* is the amount of CO_2 emissions; and *GDP* denotes gross domestic product.

From Fig. 4(b), a downwards trend in the CO_2 emission intensity of the studied cities between 1990 and 2013 was found, implying that an improvement occurred in their CO_2 emission efficiency. The CO_2 emission intensity of Tianjin had always been the highest despite declining from 58.40 tons per yuan in 1990 to 14.87 tons per yuan in 2013. Conversely, Chongqing has consistently had the lowest CO_2 emission intensity, a value which decreased from 17.33 tons per yuan in 1990 to 4.31 tons per yuan in 2013. Furthermore, Beijing is shown to have gone through a distinct efficiency improvement in terms of CO_2 emission intensity.

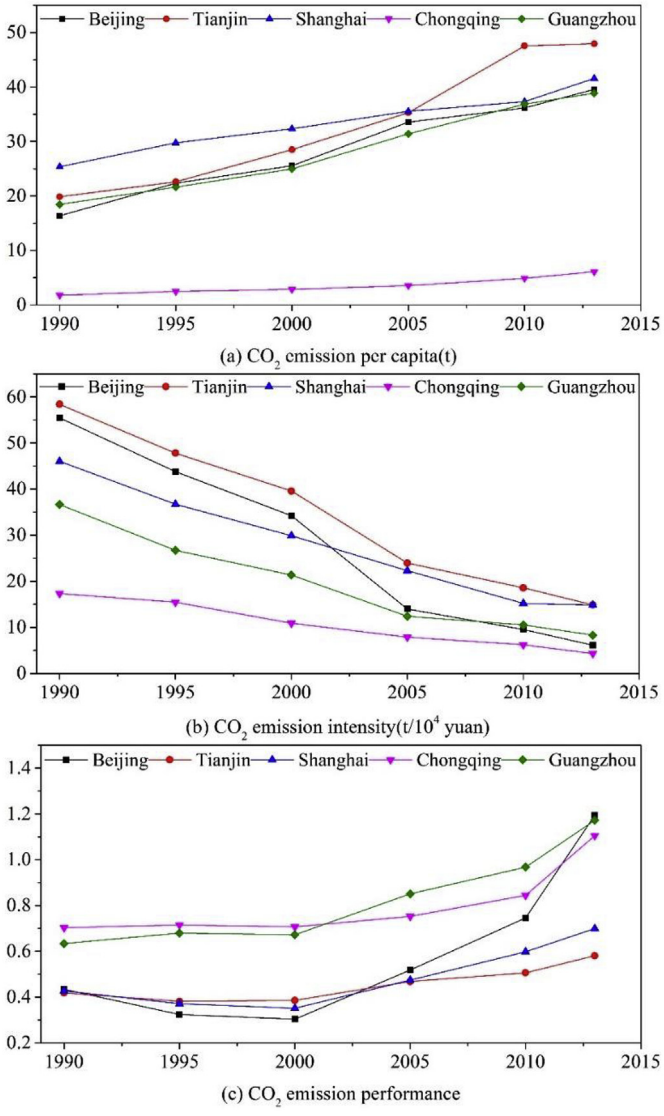

Fig. 4. CO_2 emission efficiency in the five megacities: CO_2 emission per capita (a), CO_2 emission intensity (b), and CO_2 emission performance (c), 1990–2013.

3.2.3. CO_2 emission performance

CO_2 emission performance is an indicator developed based on environmental production technology by Färe et al. (1989), which implies the joint production of undesirable outputs and desirable outputs, namely, the conversion of input vectors ($\boldsymbol{x}$) to desirable output vectors ($\boldsymbol{y}$) and undesirable output vectors ($\boldsymbol{b}$) (Färe et al., 2007), as shown in Eq. (3).

$$\boldsymbol{T} = \{(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}) : \boldsymbol{x}\ can\ produce(\boldsymbol{y}, \boldsymbol{b})\}. \quad (3)$$

Although it is an insightful idea, the environmental production technology framework is difficult to utilize directly in empirical studies. As such, data envelopment analysis (DEA) provides a practical way to model this concept (Zhou et al., 2008). Rather than forcing any rigid functional form (Kuosmanen et al., 2006), DEA use non-parametric mathematical programming techniques to evaluate overall efficiencies in decision making units (DMUs) that convert input factors into output factors (Li et al., 2007). The procedure for conducting DEA involves evaluating the technology by defining a performance standard first, then estimating achievements against the established standard (Gómez-Calvet et al., 2014). First proposed by Charnes, Cooper and Rhodes (namely, a CCR model) (Charnes et al., 1978), DEA was built on the assumption of constant returns to scale (CRS); this was subsequently developed by Banker, Charnes and Cooper (namely, a BCC model) (Banker et al., 1984), built on the assumption of variable returns to scale (VRS). Both the models mentioned above are radial DEA models, which have the limitation that all the efficiencies are estimated in the same proportion and the efficiency of the specific inputs is unable to be calculated (Choi et al., 2012). To overcome the shortcomings of radial DEA models, the slack-based efficiency measure (SBM) was introduced, which directly copes with the output shortfall and the input excess (Choi et al., 2012). Nevertheless, efficient DMUs are identified by a score of 1 in the CCR, BCC, and SBM models (Li et al., 2007), because of which plural efficient DMUs are incomparable among themselves. To discriminate between these efficient DMUs, super-efficiency was proposed for ranking the best performers (Tone, 2002).

Due to the advantages of non-radial SBM models and the idea of super-efficiency, a super-efficiency SBM model was employed to evaluate the CO_2 emission performance for the five Chinese megacities. Moreover, as the CRS assumption, which can measure the overall technical efficiency (Zha et al., 2016) and has more discrimination ability than VRS (Zhou and Ang, 2008), is adopted in most of the existing literature, the CRS assumption was adopted in this study. In this Super-SBM-CRS model, capital stock (K), labor

force (L), and energy consumption (E) were identified as inputs, while GDP (Y) and CO_2 emission (C) were identified as desirable output and undesirable output respectively, as shown in Eq. (4). CO_2 emission, the undesirable output variable in this study, was treated as an input variable, in line with the method used in a range of existing studies (Berg et al., 1992; Gomes and Lins, 2007; Hailu and Veeman, 2001; Liu and Sharp, 1999; Ramanathan, 2005; Reinhard et al., 1999; Scheel, 2001; Shi et al., 2010; Sun et al., 2013; Tyteca, 1997).

$$T = \{(K, L, E, Y, C) : (K, L, E) can\ produce (Y, C)\}. \quad (4)$$

Table 2 shows the data sources and description of the input and output variables. All the CO_2 emission performance indicators were calculated using DEA-SOLVER Pro 5.0.

Fig. 4(c) portrays CO_2 emission performances as generally increasing over time, which means that the CO_2 emission efficiency of these five megacities improved. Beijing went through the most distinct improvement in CO_2 emission performance, which increased from 0.43 in 1990 to 1.19 in 2013. In contrast, Tianjin experienced the slowest growth in CO_2 emission performance, increasing from 0.42 in 1990 to 0.58 in 2013.

3.3. Panel data analysis

Panel data analysis is a regression method that can deal with observations from multiple individuals over multiple periods (Chen et al., 2011). With both time series and cross-sectional dimensions, panel data analysis has evident advantages compared with conventional time series or cross-sectional models (Du et al., 2012), and has been widely and increasingly utilized in empirical studies. Firstly, panel data analysis can detect some factors that are difficult to be recognized in pure time series and cross-sectional data models (Ahn and Schmidt, 1995). Moreover, panel data sets usually involve more observations than time series and cross-sectional data sets, which can help reduce the effects of multicollinearity and therefore increase the degrees of freedom (Al-mulali, 2012). Thus, the efficiency of estimation can be improved by using panel data analysis. Last but not the least, panel data analysis has a high power to control unobserved heterogeneity which may result in estimation bias (Du et al., 2012). Therefore, panel data analysis was employed in this study to estimate the impacts of urban landscape pattern on CO_2 emission efficiency in five Chinese megacities. From a methodological perspective, the random effects estimator, which allows greater degrees of freedom, and the fixed effects estimator, which has relative small degrees of freedom, are two common forms of panel data models. A Hausman test is usually conducted to select more appropriate estimator (Hausman, 1978).

By reviewing the previous literature on the factors influencing CO_2 emission efficiency, this study incorporated four control variables into regression models, i.e., economic level (expressed as per capita GDP), technology level (expressed in terms of energy intensity—i.e., energy consumption per unit of GDP), industrialization level (expressed as increased value of industrial as a percentage of GDP), and population density (expressed as population per square kilometer). To eliminate heteroscedasticity and non-stationarity in the time series data, all variables underwent natural logarithm transformation (Hsiao, 2003). The specific equations for these models were as follows:

$$\begin{aligned}\ln EPC_{it} = {} & a_0 + a_1 \ln TA_{it} + a_2 \ln PAFRAC_{it} + a_3 \ln AWMSI_{it} \\ & + a_4 \ln LSI_{it} + a_5 \ln PD_{it} + a_6 \ln DIVISION_{it} \\ & + a_7 \ln SPLIT_{it} + a_8 \ln EL_{it} + a_9 \ln TL_{it} + a_{10} \ln IL_{it} \\ & + a_{11} \ln POPDEN_{it} + \varepsilon_{it}\end{aligned} \quad (5)$$

$$\begin{aligned}\ln EI_{it} = {} & a_0 + a_1 \ln TA_{it} + a_2 \ln PAFRAC_{it} + a_3 \ln AWMSI_{it} \\ & + a_4 \ln LSI_{it} + a_5 \ln PD_{it} + a_6 \ln DIVISION_{it} \\ & + a_7 \ln SPLIT_{it} + a_8 \ln EL_{it} + a_9 \ln TL_{it} + a_{10} \ln IL_{it} \\ & + a_{11} \ln POPDEN_{it} + \varepsilon_{it}\end{aligned} \quad (6)$$

$$\begin{aligned}\ln EP_{it} = {} & a_0 + a_1 \ln TA_{it} + a_2 \ln PAFRAC_{it} + a_3 \ln AWMSI_{it} \\ & + a_4 \ln LSI_{it} + a_5 \ln PD_{it} + a_6 \ln DIVISION_{it} \\ & + a_7 \ln SPLIT_{it} + a_8 \ln EL_{it} + a_9 \ln TL_{it} + a_{10} \ln IL_{it} \\ & + a_{11} \ln POPDEN_{it} + \varepsilon_{it}\end{aligned} \quad (7)$$

where i and t refer to city and year respectively, EPC denotes CO_2

Table 2
Data sources and description of the input and output variables.

Variable	Data source	Data description
Capital stock	Wu et al. (Wu et al., 2014) China Statistical Yearbook (2014) Guangdong Statistical Yearbook (2014) Guangzhou Statistical Yearbook (2014)	Prefectural capital stock data for the years 1990, 1995, 2000, 2005, 2010 and 2012 are obtained from Wu et al. (Wu et al., 2014), and capital stock for the year 2013 were estimated by using the perpetual inventory method (PIM). The data on gross fixed capital formation and the price indexes for fixed asset investment for the year 2013 were collected from corresponding statistical yearbooks, and the capital depreciation rates were developed by Wu et al. (Wu et al., 2014).
Labor force	China Statistical Yearbook (1991, 1996, 2001, 2006, 2011, and 2014) Guangzhou Statistical Yearbook (1991, 1996, 2001, 2006, 2011, and 2014)	The number of employed persons at year-end of five megacities for the years 1990, 1995, 2000, 2005, 2010, and 2013.
Energy consumption	China Energy Statistical Yearbook (1991, 1996, 2001, 2006, 2011, and 2014) Guangzhou Statistical Yearbook (1991, 1996, 2001, 2006, 2011, and 2014)	Total consumption of seven types of fossil fuels, including coal, coke, gasoline, kerosene, diesel oil, fuel oil, and crude oil, for the years 1990, 1995,2000, 2005, 2010, and 2013, all converted into tons of standard coal equivalent (TCE).
GDP	China Statistical Yearbook (1991, 1996, 2001, 2006, 2011, and 2014) Guangzhou Statistical Yearbook (1991, 1996, 2001, 2006, 2011, and 2014)	The actual GDP was converted to constant prices by using GDP indices.
CO_2 emissions	China Energy Statistical Yearbook (1991, 1996, 2001, 2006, 2011, and 2014) Guangzhou Statistical Yearbook (1991, 1996, 2001, 2006, 2011, and 2014) IPCC guidelines for national greenhouse gas inventories (IPCC, 2006)	The CO_2 emissions are computed by authors using fossil fuels use data and CO_2 emission coefficients published by the IPCC (IPCC, 2006)

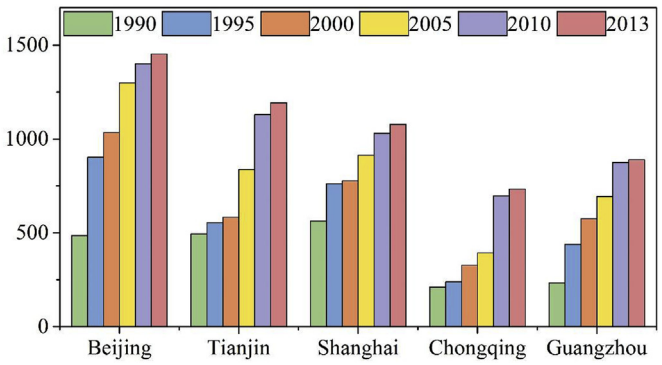

Fig. 5. Urban built-up areas of five megacities in China (km^2), 1990–2013.

emission per capita, *EI* represents CO_2 emission intensity, *EP* refers to CO_2 emission performance, *TA* is total urban area, *PAFRAC* denotes perimeter-area fractal dimension, *AWMSI* stands for area-weighted mean shape index, *LSI* represents landscape shape index, *PD* refers to patch density, *DIVISION* denotes landscape division index, *SPLIT* represents splitting index, EL denotes economic level, TL refers to technology level, IL represents industrialization level, POPDEN stands for population density, and ε is random error.

4. Results and interpretations

4.1. The dynamics of urban landscape pattern, 1990–2013

Due to the accelerating urbanization, Beijing, Tianjin, Shanghai, Chongqing, and Guangzhou experienced significant changes in their urban landscape patterns between 1990 and 2013. As shown in Fig. 5, which plots the urban areas of these five Chinese megacities for the selected years, the total urban area (TA) of each megacity expanded rapidly between 1990 and 2013. In 1990, the largest urban area (Shanghai) and the smallest urban area (Chongqing) were 562.46 km^2 and 210.61 km^2 respectively, while in 2013 the largest and smallest urban areas had increased to 1452.38 km^2 (Beijing) and 733.02 km^2 (Chongqing) respectively. Beijing experienced the greatest urban expansion, with its urban area increasing from 484.87 km^2 in 1990 to 1452.38 km^2 in 2013 (an increase of 967.51 km^2), while Shanghai, whose urban area increased from 562.46 km^2 in 1990 to 1078.09 km^2 in 2013 (an increase of 515.63 km^2), experienced the least expansion.

With the help of remote sensing data and landscape metrics, a range of indicators namely, PAFRAC, AWMSI, LSI, PD, DIVISION, and SPLIT—were computed individually for each city. The results of this calculation show significant discrepancies between cities in terms of the magnitudes of indicators, but the same basic change trend. As shown in Fig. 6(a)–(c), PAFRAC, AWMSI, and LSI, which measure the shape complexity of a given urban landscape, increased during the study period in each of the five megacities, a finding that suggests that the urban landscape adopted a more irregular and convoluted pattern in these megacities between 1990 and 2013. In terms of urban compactness, Fig. 6(d)–(f) reveal that PD, DIVISION, and SPLIT conformed to decreasing trends between 1990 and 2013 in each of the five megacities, a finding that may indicate that the urban landscape of these five megacities became more compact—so, whilst the urban landscape of each megacity expanded through merging with existing urban areas, this created a more continuous urban patch.

4.2. The impact of urban landscape pattern on CO_2 emission efficiency

In a multiple regression model, multicollinearity is a situation in which explanatory variables are linearly dependent (Wang et al., 2013b). Before conducting the panel data analysis, a multicollinearity test was conducted to see whether multicollinearity existed among the seven landscape metrics. As indicated in Table 3, no severe multicollinearity exists among the seven selected landscape metrics. As thus, parameter estimations of the panel data models can be conducted.

Hausman tests were conducted, whose null hypothesis is that random effects estimator is more suitable, to determine the appropriate form for the panel data models. As indicated in Table 4, the *P* values of Model I and Model III were greater than 0.05, without rejecting the null hypothesis, which indicated that the random effects estimator were more suitable for Model I and Model III. Whereas, the *P* value of Model II was less than 0.05, rejecting the

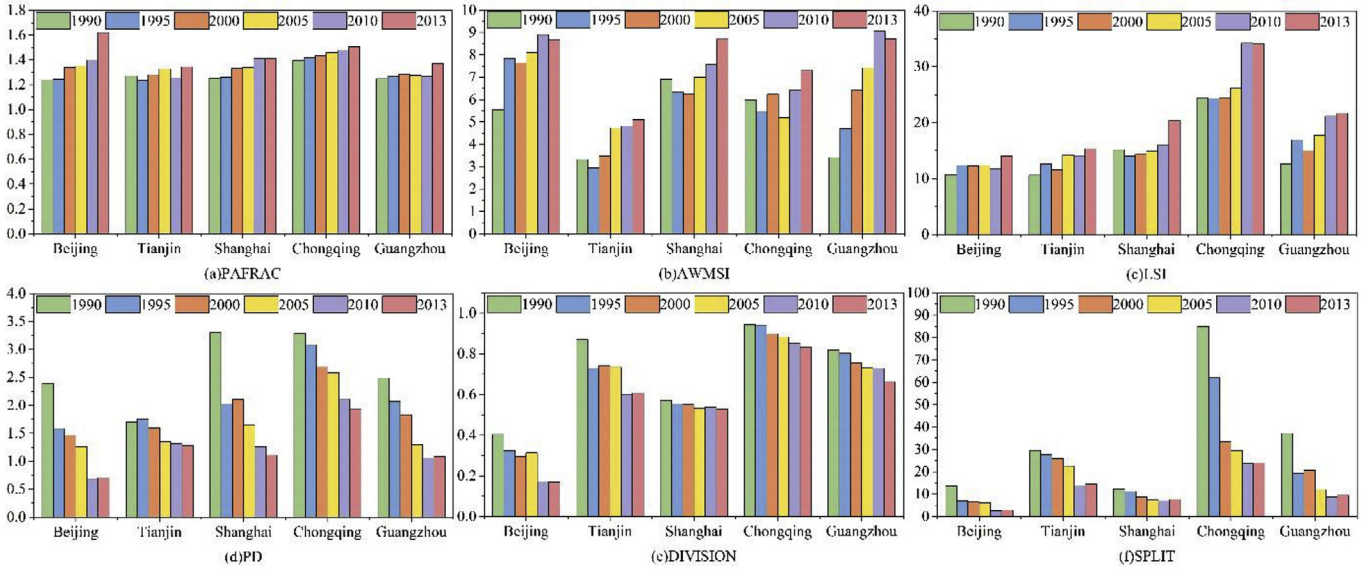

Fig. 6. Changes in landscape metrics in five megacities in China, 1990–2013.

Table 3
Pearson's correlation coefficients of the independent variables.

	TA	PAFRAC	AWMSI	LSI	PD	DIVISION	SPLIT
TA	1						
PAFRAC	−0.652***	1					
AWMSI	0.287	0.092	1				
LSI	0.097	0.166	−0.257	1			
PD	−0.792***	0.734***	−0.294	0.241	1		
DIVISION	−0.683***	0.253	−0.675***	0.268	0.501***	1	
SPLIT	−0.334*	0.14	−0.494***	0.367**	0.319*	0.612***	1

***p < 0.01, **p < 0.05, *p < 0.1.

Table 4
Hausman test results.

	Chi-Sq statistic	*P* values	Type of regression model
Model I	2.68	0.9943	Random effects
Model II	53.73	0.0000	Fixed effects
Model III	1.79	0.9991	Random effects

null hypothesis, indicating that fixed effects estimator should be employed for Model II.

From Table 5, which exhibits the results of parameter estimation, the impacts of urban landscape pattern on CO_2 emission efficiency can be identified. Model I was used to test the effects of urban landscape pattern on CO_2 emission per capita. Results reveal that DIVISION and SPLIT exerted a significant positive effect on CO_2 emission per capita, a finding that was consistent with expectation. As mentioned previously, the indicators DIVISION and SPLIT are measures of urban compactness, which represents the degree to which urban patches are scattered. In general, the higher the values of DIVISION and SPLIT, the less compact the spatial pattern of urban landscape. As thus, the estimation results of Model I could be interpreted as that more compact urban landscape pattern results in lower CO_2 emission per capita, i.e., higher CO_2 emission efficiency. As CO_2 emission per capita is defined as the ratio of CO_2 emission to population, it is determined by these two aspect simultaneously. On the one hand, a mounting number of studies have addressed the ways in which compact urban landscapes can mitigate greenhouse effects (Anderson et al., 1996; Dhakal, 2009), and come to the conclusion that compact urban structure would help to reduce CO_2 emissions (Ergas et al., 2016; Kennedy et al., 2009; Vaccari et al., 2013). On the other hand, cities with compact urban landscape pattern are generally densely-populated, that is, more compact urban landscape pattern would lead to a larger population. To sum up, compact urban landscape pattern is conducive to the reduction of CO_2 emission per capita, which is regarded as an improvement of CO_2 emission efficiency, as it results in both less CO_2 emissions and larger population.

Table 5
Estimation results for different panel models.

Explanatory variables	Model I	Model II	Model III
Focal variables			
ln TA	10.22	48.13	−0.547**
	(8.432)	(17.42)	(0.468)
ln PAFRAC	4.154	93.22	−0.376**
	(23.23)	(39.46)	(1.288)
ln AWMSI	2.130	−0.976	−0.0690**
	(1.282)	(1.593)	(0.0711)
ln LSI	−0.261	−0.730	−0.0366**
	(0.326)	(0.595)	(0.0181)
ln PD	7.052	21.72***	−0.619***
	(5.950)	(8.178)	(0.330)
ln DIVISION	65.13***	73.05***	0.624
	(24.88)	(45.46)	(1.380)
ln SPLIT	0.337***	0.0788	−0.0120***
	(0.0669)	(0.113)	(0.00371)
Control variables			
ln EL	13.68***	−0.668***	0.336**
	(5.093)	(4.653)	(0.282)
ln TL	1.718	5.183***	−0.0364***
	(1.290)	(1.202)	(0.0715)
ln IL	10.17	17.87**	−1.168**
	(18.27)	(32.88)	(1.014)
ln POPDEN	−3.646**	−17.02*	−0.0473
	(2.144)	(9.595)	(0.119)
Constant	−304.0*	−621.8*	−8.864
	(139.4)	(261.4)	(7.733)
R-squared	0.957	0.979	0.914

***p < 0.01, **p < 0.05, *p < 0.1.

Model II specified the correlation between urban landscape pattern and CO_2 emission intensity, which is expressed as CO_2 emission per unit GDP. As indicated in Table 5, PD and DIVISION, two indicators measuring urban compactness, were found to positively correlate with CO_2 emission intensity, a ratio-based indicator combining CO_2 emission with economic growth. From the perspective of CO_2 emission, compact urban spatial structure is beneficial for reducing CO_2 emission and increasing carbon sequestration, and ultimately results in less ambient CO_2, due to increased accessibility, less need to drive, full utilization of existing infrastructures, and the conservation of green spaces, all of which are caused by compact urban landscape pattern (Ewing et al., 2007; Gordon and Richardson, 1997). With respect to economic growth, compact urban form could foster urban economic development and increase GDP, due to agglomeration economies, that is, that the spatial clustering of economic activities can lead to positive externalities (Melo et al., 2009), including more efficient sharing of infrastructure and facilities, better matching between employers/buyers and employees/suppliers, or business partners, and more accesses to the transmission of new technologies and business practices, i.e., substantial innovations. In a word, more compact urban landscape pattern helps to reduce CO_2 emission as well as increase GDP, as thus, it would lower CO_2 emission intensity, i.e., improve CO_2 emission efficiency in terms of economic growth.

Through Model III, this study estimated the impact of urban landscape pattern on CO_2 emission performance. The results indicate that TA, PAFRAC, AWMSI, LSI, PD, and SPLIT demonstrated negative impacts on CO_2 emission performance, a total-factor efficiency measurement based on input-output analysis. TA was found to exert a significant negative effect on CO_2 emissions performance, namely that urban expansion inhibits CO_2 emission efficiency improvement. Since the late 1970s, millions of rural residents have migrated to cities due to the “reform and opening-up” policy, which resulted in accelerating urbanization in China. It is commonly known that urban lifestyles are more energy-intensive than rural lifestyles, which is exemplified in the way in which automobile-dependent urban sprawl has contributed significantly to the combustion of fossil fuels and exhaust emissions (Bart, 2010). Hence, urban expansion stimulated tremendous demand for energy and consequently greater CO_2 emissions, indicating that more undesirable output is produced. Moreover, as every city had its own optimum size for operational efficiency, once outgrowing this optimum size, it started to experience diseconomies of scale. Specifically, cities with oversize urban area were difficult to coordinate effectively, and overcrowding as well as facility congestion arose. As a result, marginal costs started to increase, i.e., to output the same amount of GDP, more inputs, including capital, labor force, and energy, were needed. Ultimately, the combination of more undesirable output and more requirements of input factors resulted in decreasing CO_2 emission performance. PAFRAC, AWMSI, and LSI, the three urban shape complexity measurement exerted inhibitory

effects in relation to CO_2 emission performance. Urban shape complexity is interpreted as the degree of the geometry of urban patches being convoluted, which could increase the possibility of traffic congestion. Characterized by lower velocities, longer travel time, and aggravated vehicular queuing (Ang, 1990), traffic congestion could raise fuel consumption as well as exhaust emissions. Therefore, more undesirable outputs, i.e., CO_2 emissions, are produced. Furthermore, complex urban landscape pattern could decrease the operational efficiency of the urban transportation system, and is thus detrimental to the integration of input factors and the output of GDP. Hence, CO_2 emission performance decreased as the urban form displayed increasingly irregular and complex spatial patterns. The coefficients of PD and SPLIT were also negative, suggesting urban compactness positively influenced CO_2 emission performance. As interpreted in results of Model I and Model II, compact urban landscape pattern is a low-carbon spatial form, which could decrease the undesirable output of CO_2 emissions. In addition, according to the theory of agglomeration economies, enterprises are able to produce more output with the same inputs in high-density urban environments. Economic activities in compact cities are thus more productive, which makes compact cities have productivity advantages. With less CO_2 emissions and higher productivity, compact cities generally have higher CO_2 emission performance.

4.3. The optimal urban development patterns for improving CO_2 emission efficiency

The empirical results revealed that urban expansion and urban shape complexity inhibited, while urban compactness benefited, the improvement of CO_2 emission efficiency, however, due to ongoing economic development and urbanization process, urban growth is a natural and inevitable trend over the next several decades in China. Therefore, the optimal urban growth for improving CO_2 emission efficiency should be leapfrog and under planning control, which can be summarized as “smart growth”. To be specific, four archetypical urban development patterns are proposed, including infill development, polycentric development, transit-oriented development, and environmentally-friendly development.

4.3.1. Infill development

Spatial structure (i.e., the morphological and functional organization of cities) has significant impact on urban CO_2 emissions. The optimization of spatial structure lowers CO_2 emissions mainly by affecting residents' travel behaviors and accordingly reducing mobility. Urban infill development, which accentuates the concept of “compact city”, is believed to have land use efficiency advantages and benefit the reduction of CO_2 emissions. To be more specific, infill development means increasing density, public transit availability, and land use mix for urban areas, which will improve the accessibility and diversity of housing, employment, and services, and thus decrease residents’ daily travel distances and associated CO_2 emissions.

4.3.2. Polycentric development

Since low-density suburbanization is more dependent on automobile use and consequently brings about more exhaust emissions, polycentric development (i.e., leapfrog development), an effective spatial configuration in terms of preventing cities from unlimited sprawl, should be adopted to reduce CO_2 emissions. Unlike monocentric development, which is characterized by a single downtown area with multiple functions, polycentric development aims to foster multiple subcenters with diverse functions, which are relatively independent of the downtown area. As most of the residents’ daily activities are kept inside each subcenters, constrained mobility and associated CO_2 emissions can be mitigated. For example, the job–housing balance can be improved by polycentric development, which is able to decrease long distance commutes and associated CO_2 emissions.

4.3.3. Transit-oriented development

As is well known, exhaust emission (including CO_2) per passenger of private vehicles is much higher than that of public vehicles, and public transport is thus less carbon-intensive and more environmentally sustainable than private transport. As thus, transit-oriented development (TOD), whose essence is reducing vehicle miles traveled (VMT) by improving accessibility of housing, employment, and services facilities, is regarded as an effective way to reduce CO_2 emissions. The characteristic of TOD can be summarized as “3D”, i.e., “Density-Diversity-Design”. “Density” means that areas with high accessibility to public transport stations should be given priority for development as well as high development intensity, in order to increase modal share of public transit. “Diversity” refers to mixed land use at station areas, i.e., the proximity of housing, employment, and services facilities, which can decrease VMT. “Design” refers to pedestrian-friendly urban design for improving the connectivity among different means of transportation, which creates comfortable environment for cycling and walking.

4.3.4. Environmentally-friendly development

All of the above three urban development patterns aim to achieve CO_2 emission abatement, focusing on the “source” aspect. However, atmospheric CO_2 depends on not only carbon sources but also carbon sinks. Therefore, increasing carbon absorption is also an important approach to realize low-carbon urban development. Natural environment, mainly forest and ocean, constitutes the majority of global carbon sinks, because of which urban development patterns at the expense of natural environment should be ruled out. Take coastal cities for example, it has been proved that coastal ocean have some carbon sinking effects (Bauer et al., 2013; Cai, 2011; Laruelle et al., 2018), hence, the utilization of coastal areas should be regulated and the destruction of coastal eco-environment should be forbidden. Moreover, policy instrument, such as urban growth boundary (UGB), should be employed to preserve coastal eco-environment and promote environmentally-friendly urban development.

5. Conclusions and discussions

Global warming, which principally results from CO_2 emissions, has been unanimously recognized as a serious threat to global sustainability. To tackle the challenge of global climate change, the academic community has investigated approaches to increasing CO_2 emission efficiency from a range of socioeconomic perspectives. Mounting attention has also been paid to the importance of spatial optimization measures and urban planning practices in reducing CO_2 emissions (Chuai et al., 2015), and recent literature has begun to discuss the impacts of urban landscape pattern or urban form on CO_2 emission tonnages. Despite the individual merits of these two bodies of literature, the impact of urban landscape pattern on CO_2 emission efficiency is not yet fully understood. Realizing this deficiency in existing literature, this paper aimed to explore the associations between urban landscape pattern and CO_2 emission efficiency, using panel data for five megacities in China, namely Beijing, Tianjin, Shanghai, Chongqing, and Guangzhou, for the period 1990–2013.

In this study, several landscape metrics quantified based on remote sensing data, were first selected to evaluate three

dimensions of urban landscape pattern (urban expansion, urban shape complexity, and urban compactness) for five megacities in China. Three quantitative indicators—per capita CO_2 emission, CO_2 emission intensity, and CO_2 emission performance—were then calculated, in order to examine CO_2 emission efficiency. Panel data models were subsequently implemented to explore the impacts of urban landscape pattern on CO_2 emission efficiency. Before establishing panel data models, a multicollinearity test was conducted and the test results indicate that no high correlations existed among the seven landscape metrics variables. In order to decide whether the random effects estimator or the fixed effects estimator was more appropriate for each of the three panel data models, a Hausman test was implemented.

From the analysis of dependent variables, it was found that when CO_2 emission efficiency was addressed in terms of per capita CO_2 emission, it decreased in all five of the megacities studied between 1990 and 2013, while when CO_2 emission efficiency was represented by CO_2 emission intensity and CO_2 emission performance, it increased. As to the explanatory variables, it demonstrated that the total urban areas of each city have experienced rapid growth from 1990 to 2013. Moreover, PAFRAC, AWMSI, and LSI of each city were shown to have increased, while PD, DIVISION, and SPLIT were found to have declined, which signifies that urban landscape patterns of the five megacities involved in this study became more convoluted and more compact. The parameter estimation results demonstrated that TA was negatively correlated with CO_2 emissions performance, indicating that urban expansion inevitably decreases CO_2 emission efficiency. This result was ascribed to more undesirable output of CO_2 emissions arising from accelerating urbanization and more requirements for input factors arising from diseconomies of scale, both of which were due to urban expansion. Similarly, the variables PAFRAC, AWMSI, and LSI were all found to be negatively correlated with CO_2 emission performance, which implied that urban landscapes with irregular shapes are inhibited with respect to improvement in CO_2 emission efficiency. A possible reason for this phenomenon is that urban landscapes with highly convoluted geometries bring about more undesirable output of CO_2 emissions by increasing the duration and distance of common commuting, and are detrimental to the integration of input factors and the output of GDP by decreasing the operational efficiency of the transportation system. More importantly, indicators measuring urban compactness were found to positively correlate with CO_2 emission per capita and CO_2 emission intensity, while negatively correlate with CO_2 emission performance, all implying that compact urban development is conducive to improving CO_2 emission efficiency. This result were interpreted from four aspects, i.e., CO_2 emission, population, GDP, and input-output efficiency. From the perspective of CO_2 emission, compact urban form is an energy-saving and low-carbon spatial structure and helps to reduce the undesirable output of CO_2 emissions. In terms of population, cities with more compact urban landscape pattern are generally more densely-populated and have a larger population. With respect to GDP, compact urban form could foster urban economic development and increase GDP, due to agglomeration economies. As to input-output efficiency, economic activities in compact and high-density urban environments are believed to be more productive, which makes compact cities have productivity advantages. In conclusion, as more compact urban landscape pattern results in less CO_2 emissions, larger population, increasing GDP, and higher productivity, it is believed to be conducive to the reduction of CO_2 emission per capita and CO_2 emission intensity, as well as the improvement of CO_2 emission performance.

At present, as the world's biggest developing country, China still needs to maintain steady economic growth. While the Chinese government have promised to deliver a peak in the country's CO_2 emission level before 2030, this will almost inevitably have a negative impact on economic growth. Given these conditions, Chinese policy makers face a dual challenge in mitigating CO_2 emissions and maintaining sustaining steady economic growth—improving CO_2 emission efficiency is an effective way to maintain a balance between these two goals. In addition to previous studies, which have tackled CO_2 emission efficiency by addressing socioeconomic considerations, this study highlighted the significance of city planning and the optimization of spatial structure as effective alternatives in improving CO_2 emission efficiency. A range of meaningful policy implications can be extracted from these results with respect to low-carbon urban planning's aims to realize urban sustainable development. First, the rapid expansion of urban areas should be controlled by promoting sustainable growth in terms of urban land and pursuing optimal urban sizes. Given that green spaces playing a crucial role in stocking carbon sinks, city authorities should encourage the development of urban agriculture (Kulak et al., 2013; Lee et al., 2015). Urban planners should also work to conserve green areas during the processes of suburban development. Furthermore, public low-carbon awareness should be strengthened in order to support a shift towards sustainable lifestyle. Second, urban planners should optimize the shape of urban areas to be more regular when designing the urban layouts. Urban form can influence the operational efficiency of the urban transportation system by affecting the travel behavior of residents, which ultimately impacts on CO_2 emissions (Camagni et al., 2002). In terms of shape complexity, namely the jaggedness of a landscape, urban areas with regular geometries can reduce transportation demand and the use of automobiles, resulting in more efficient transportation systems. Urban CO_2 emission efficiency can therefore be improved by lowering urban shape complexity. Third, the concepts of both the “compact city” and “smart growth”, which envision future cities characterized by mixed land use, high density, and transit-oriented and pedestrian-oriented development (Chen et al., 2008), should be employed in urban planning and spatial optimization; this would assist greatly in the aim to raise CO_2 emission efficiency and build low-carbon cities. The reason why measures to increase urban compactness can improve CO_2 emission efficiency lie in the fact that compact urban development produces less CO_2 emissions than decentralized urban development, and “smart growth” is more sustainable than urban sprawl. Specifically, as a result of efficient public transportation systems and large-scale green spaces, walking and cycling are prevalent in compact cities, which results in turn in energy conservation as well as CO_2 emission mitigation. In summary, the empirical findings obtained through this study provide assistance for decision makers and urban planners in identifying effective spatial strategies for CO_2 emission efficiency improvement, and contribute to the scientific basis for building low-carbon cities in China.

On the basis of this study, it might prove fruitful to further investigate how urban landscape pattern affects CO_2 emission efficiency at smaller scales, using different methods, and from different perspectives. Several future study directions are thus proposed as follows. Firstly, the estimation of the correlation between built environment and CO_2 emission efficiency could be extended from landscape-level to class-level and patch-level. Landscape analysis can be conducted at three different levels, i.e., patch-level, class-level, and landscape-level. In urban landscape pattern studies, every single urban land parcel is regarded as a “patch”; a certain type of urban land uses, such as residential, commercial, and industrial uses, is regarded as a “class”; and all the urban area is regarded as a whole “landscape”. It is necessary to point out that different urban land parcels and different urban land use types are likely to perform differently in CO_2 emission

efficiency, how urban form affects CO_2 emission efficiency may therefore vary with different levels. However, it is nearly impossible to identify such land uses in Landsat ETM and Landsat TM scenes with a spatial resolution of 30 m. Hence, more data are expected to utilize in future studies so that this research topic can be addressed much better. Moreover, other models and techniques could also be applied in future studies to quantify the association between urban landscape pattern and CO_2 emission efficiency. According to Tobler's First Law of Geography, all attribute values on a geographic surface are related to each other, and closer attribute values are more strongly related than more distant ones (Tobler, 1970). Therefore, spatial regression models, which take into account the spatial autocorrelation of geographic data, could be used to more fully identify the interactions between urban landscape pattern and CO_2 emission efficiency in different geographical units. In addition to spatial regression models, the simulation method (Li and Yeh, 2000) is another considerable technique to address the correlations between changing urban landscape pattern and CO_2 emission efficiency in future studies, based on which experiments can be performed and replicated in a standard platform to assess self-organizing and non-linear dynamics of complex systems like cities (Wu, 1999). Last but not least, in order to investigate the diverse effects of urban landscape pattern on CO_2 emissions for cities with different development levels, more Chinese cities could be introduced into relevant studies, particularly cities at different stages of development. In addition, this study was confined to China, but similar researches are worth conducting in the context of other countries and might yield different and interesting results. In other words, future studies could explore the links that exist between urban landscape pattern and CO_2 emission efficiency from a more international perspective and make a comparison between developing countries and developed countries.

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